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Facial Gender Classification with Local Directional Pattern

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Abstract
In this paper, a new approach for gender classification is presented. The human face serves as a knowledge base for useful demographic information such as gender, age and expressions. We can easily identify the gender of the person, but it is difficult for the machine to recognize gender from the face image. The face is a complex three dimensional object and it is a difficult task for automatic recognition of the gender due to a wide degree of variations in texture and shape of the face. The support vector machine classifier is used for gender classification. The experiment is carried out using Caltech, Yale, Orl and Lfw face data sets. The result shows that improved gender classification accuracy with the local directional pattern approach and the principal component analysis. The average accuracy of the gender classification is 96%.

Keywords: *Face Gender, local directional pattern, Principal Component Analysis , Local Binary Pattern .*

Nomenclature

LDP	local direction Pattern
LBP	local Binary Pattern
PCA	Principal Component Analysis
ICA	Independent Component Analysis
SVM	Support Vector Machine

1. Introduction

Face is a representation of the identity of a person. There are several ways of the identification by which the information about an individual is obtained. The visual information and textual information are the two important representations of the person identification**.** The visual image of the face provides an important information source for gender, age and shape classification. The texual information such as name, address etc. The gender and demographic information always remain the same while age and shape changes with respect to the time[17]. The face gives the identification of the individual person and it indicates the state of the mind, emotions etc. The problem of the face detection and recognition has been studied past several years and finds potential application in the areas of human computer interaction systems, security surveillance systems, content based indexing and searching, searching for the person or the missing person[6]. The analysis of face images leads an important role in many computer vision applications. The face is a unique and important feature of human beings and carries an identification of the individual[5]. Humans have the robust ability to determine gender from facial images even if the face is cropped or some part of the face removed. Recently, due to wide potential applications of the identification of the gender by the machine has got more importance in automatic processing of the information**.**

The gender classification based on the facial images is one of the challenging problems in image analysis applications due variations in the image illumination and occlusion[8]. The problem of the gender classification of the face image is proposed in this paper.

We can easily identify the gender of the person from the face image, but the situation is different for automatic recognition of the gender by the machine. The face gender detection is a binary classification problem. The identification of the gender in any application reduces the problem to half of the data population and similarly the age information of the individual helps in the faster identification or searching for the person by the different ethnic groups[7]. The face is homogeneous in nature, but the internal variations in the features which may affect the accuracy of the computer vision systems to recognize as gender.

The paper is organized in the following sections. The section 2 describes the theoretical background for the local directional pattern, principal component analysis and local binary pattern. The support vector machine classifier for the face image gender classification. The section 3 concludes the paper with a discussion on the gender classification accuracy.

2. Theory

The gender classification has received considerable attention over the past years, both for its potential contribution to face recognition as well as its applications in human computer interaction. The details of the block diagram for the classification of gender from face image is shown in figure 1.

The gender classification is performed by dividing the classification problem in the following steps. The face detection and normalization for the variation in the size and illumination. Then the features are extracted from the face and classified using labelled data. The most of the approach for classifying gender differ in the above steps. The feature extraction of the face image is divided into two types such as geometry based methods and appearance based methods[3].

2.1. Geometry based methods

The geometric based methods for the feature extraction use geometric features e.g. Face width, length, mouth size, eye size and different angles. The geometrical method calculates the distance between facial landmarks such as the distance between two eyes, nose, mouth etc.
It also finds the geometrical relation between different landmark points and performing the some ratio calculations as features for the classification.
In geometry based method the accuracy of a locating landmark point plays a major role. A.R. Ardakany and A.M. Joula[1] explored geometrical and appearance feature extraction method for gender classification. The features are analyzed using histogram of edge magnitudes and direction. The result of the experiment on the FERET database with 95.6 % accuracy. S. Ravi and S. Wilson [18] addressed the problem of face detection and gender classification in color images. Initially face is detected in an image using skin color.
The preprocessing of the face image performed by converting the color image into the gray scale image. The face is detected using voila Jone method[14] for the face detection then the other features are extracted such as left eyes, right eyes, nose and mouth from the face image. The geometrical method of the face gender classification based on the geometrical related information regarding the face features for the classification [20].

2.2. Appearance based methods

The appearance based methods for feature extraction are developed using some operations of transformation performed on the image. These methods based on the whole image called as global appearance or based on the local regions(of the face image) called as local appearance. The appearance of the face image used for classification of the gender based on the boundary between the male and female face classes. Huchuan Lu et. al. [9] proposed pixel pattern based textual features for real time gender recognition. A grayscale image is converted into pattern map to represent lines and edges as texture information. The feature vector is derived from the pattern map. The principal component analysis based technique is used for pattern matching and with the adaboost most discriminating feature subset is selected. The gender of the frontal image is classified by using support vector machine.
The two most standard methods used to reduce the dimensionality of the feature set are linear discriminant analysis and principal component analysis. The principal component analysis finds the direction of the maximum data variance axis. The linear discriminant analysis finds the class separation information between the two classes.

Cheng Quanhua et al[4]. used technique of Eigen faces and least squares support vector machine (LS-SVM) classification of the gender. The face training images are projected into the eigenface and eigenface coefficients are calculated. The least square support vector machine used for classification of face from the training and testing images. The result shows that LS-SVM classification has better performance than the other classification algorithm.
The local binary pattern is proposed for the texture description and widely used for many applications including face detection, face recognition , gender and age classification. The local binary pattern is computationally simple and gives local spatial structure of an image. However, it shows poor performance in the case of the random noise. The LBP operator gives labels to the pixels of the image by threshodling 3x3 matrix neighborhood of each pixel with central value and converting these values into the binary number. This binary bit pattern generated is called as local binary pattern [21].
Hui-Cheng Lian and Bao Liang Lu[10] described multi view gender classification using local binary pattern. The features are extracted and represented in the histogram as single vector. The classification is performed using support vector machine. They have used Caspeal database and reported gender classification rate of 96.75%. Srinivas Gutta et. al [17] presented gender and ethnic classification of the pose using a mixture of expert. The mixture of experts consists of (RBFs). Inductive decision trees (DTs) and support vector machines (SVMs). The experimental results indicate an gender classification accuracy reported of 96% using the ERBF/DT method from frontal face images, while the the svm gives 100% on pose classification.
The experiment performed by Jain et al [11] for frontal face images using independent component analysis of the face images and the feature vector is represented by the ICA feature space. The gender classification performed on 500 images 250 for male images and 250 for the female images. The support vector machine classifier is used for the gender classified. They have achieved result of 96 %.
The feature vector plays very important role for the describing the object. But some of the features of object are important and some are less important. The idea of the feature selection based on the mutual information for the measurement of the relevant and redundant features and gender classification experiment performed by Juan et al.[12]. The gender classification experiment is performed using local binary pattern histogram (LBPH) for different radii and different scales. The three different features such as intensity , texture and features used for the gender classification with the four face database. The information theory based feature selection, fusion and mutual information measurements such as minimum reduancy and maximum releavence, conditional mutual information selection and conditional mutual information maximization are used for feature representation.
The feature data set determines the size of the training data set used for the training the supervised classifier such as support vector machine. Ramesha et al. [15]

addressed the issue of the limited training data set or even with the single image for one person. The facial features are extracted using the canny edge operator for the edge detection. The artificial neural network is used for the classification of the gender and age with the posterior probability. The accuracy for the gender classification achieved of the 98 %.

Rodrigo Verschae et al.[16] developed framework for the domain partition classifier and adaboost for the gender classification. The gender classification is performed using different types of features such as a local binary pattern, wavelet and rectangular. The gender classification performed on the database of the images FERET and BioID.

The feature selection and information fusion technique are used for gender recognition. The improvement in the result is shown due to the selection of the features using mutual information. The results are tested on the databases of unconstrained images. The information given by the psychological experiment shows that the chin of the face carries more information than other part of the face [5].

2.3. Methodology

The gender recognition has many applications for human to machine interface. The interface provides the appropriate necessary information to the machine. The face images are preprocessed for removing the noise. In order to classify the face gender, it is required to segment the face image from the background. Viola Jones[14] method for face detection is used to find the region of the face. Then to segment the facial region from the image, the face region is cropped. The histogram equalization is used for face image normalization to reduce the illumination. The size of the face is normalized to the standard face size of 100x100 pixels and stored in the training data set. The details of the block diagram for gender classification is shown in figure 1. The features for gender classification extracted using local binary pattern and local direction pattern. The histogram of the local binary pattern is stored in as features vector. Similary, The local directional pattern features are stored as a histogram of the feature vector. The principal component analysis is used on these feature vectors to reduce the dimensionality of the feature vector. The flow chart for the gender classification is shown in figure 9.

2.3.1 Local Directional Pattern

The local directional pattern operator works on the edge response values of the neighboring pixels of 3x3 matrix and encodes the image texture.

Local directional pattern encodes the structure of the local neighboring pixels in eight different directions with a compass Kirsch mask as shown in figure 2. The positive and negative edge responses provide valuable information because it gives a change of intensities from light to dark or dark to light in the texture and gradient direction of bright and dark area in the neighborhood. It holds relation amount the pixel implicitly, due to these relation gradient space reveals underlying structure of the image. The gradient space has more discriminating power to discover key special features[6]. The local directional pattern descriptor uses more information as compared to the LBP operator which uses only sparse coding. The 8-bit binary code is assigned to each pixel in the image. The edge response of the neighboring pixels is computed by using Kirsch compass mask.

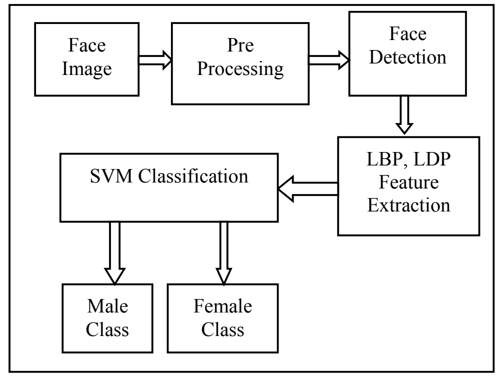

Figure 1: Face Gender Classification System

The Krisch detector captures the edge information from the pixel in the centre of the 3x3 matrix. There are eight direction edge responses are calculated from the values m_i = 0 to 7. This is shown in figure 3. The edge responses are prominent in presence of corner or high edge response values in some particular direction. The local direction pattern encode directional information in the neighborhood of the central pixels in the matrix of 3x3. The local direction pattern code is generated based on the most prominent directional numbers with high response values. The local direction pattern code is given by equation (1). The local direction pattern code from all the direction, top positive and negative directions are selected to produce meaningful descriptor for different texture with similar structure pattern. The example of the local directional pattern is shown in figure 4.

$$LDP=\sum_{i=0}^{7} bi(mi-mk)\,x^{2i} \tag{1}$$

$$\underset{M0}{\begin{bmatrix}-3 & -3 & 5\\ -3 & 0 & 5\\ -3 & -3 & 5\end{bmatrix}}\underset{M1}{\begin{bmatrix}-3 & 5 & 5\\ -3 & 0 & 5\\ -3 & -3 & -3\end{bmatrix}}\underset{M2}{\begin{bmatrix}5 & 5 & 5\\ -3 & 0 & -3\\ -3 & -3 & -3\end{bmatrix}}\underset{M3}{\begin{bmatrix}5 & 5 & -3\\ -5 & 0 & -3\\ -3 & -3 & -3\end{bmatrix}}$$

$$\underset{M4}{\begin{bmatrix}-5 & -3 & -3\\ 5 & 0 & -3\\ 5 & -3 & -3\end{bmatrix}}\underset{M5}{\begin{bmatrix}-3 & -3 & -3\\ 5 & 0 & -3\\ 5 & 5 & -3\end{bmatrix}}\underset{M6}{\begin{bmatrix}-3 & -3 & -3\\ -3 & 0 & -3\\ 5 & 5 & 5\end{bmatrix}}\underset{M7}{\begin{bmatrix}-3 & -3 & -3\\ -3 & 0 & 5\\ -3 & 5 & 5\end{bmatrix}}$$

Figure 2 : Krisch Edge Mask

M3	M2	M1
M4	C	M0
M5	M6	M7

Figure 3: Mask response and LDP bit position

20	52	63
59	78	45
25	48	71

-101	-69	131
-317	78	283
-93	113	163

0	0	1
0	X	1
0	1	1

Local directional pattern : 11000011

Figure 4: Local Directional Pattern

The local directional pattern for the face image is shown in the figure 5. The face image code for each pixel derived using the equation (1). The feature vector is represented using the local directional pattern. The feature vector is represented as a histogram of the local direction face image.

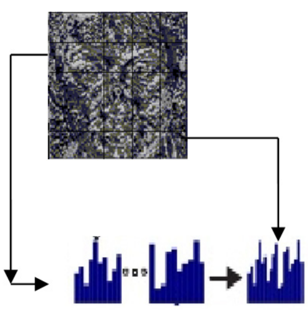

Figure 5: LDP image and LDP histogram

2.3.2 Local Binary Patterns

The local binary pattern is the binary pattern derived from the local neighbors of the central pixel. The local binary pattern used to represent the image in terms of the pixel intensity difference. It is widely used for extracting local region texture of the image. It used in the applications like feature extraction, face recognition[19] etc.

The local binary pattern basically represents the local structure of the image by calculating the difference between the central pixel and surrounding pixels in the matrix of 3x3[2]. The intensity of the central pixel is compared with the neighboring pixel are according if the intensity of the neighboring is greater than it is repsented as 1 else it is represented as 0 in the binary pattern using the equation (2). Thus ,each neighbor receives the coding bit as 0 or 1 and 8 bit pattern is assigned to the neighboring pixels as shown in figure 6.

$$LBP(x_c, y_c) = \sum_{n=0}^{7} s(i_n - i_c)2^n \qquad (2)$$

The local binary pattern features for the face image is shown in figure 7. Local directional pattern for face image is derived from the thresholding the central pixel value with neighboring pixels using the equation

1	2	2
9	5	6
5	3	1

0	0	0
1		1
1	0	0

Local binary pattern : 00110001

Figure 6 Local Binary Pattern

The local binary pattern is represented by the histogram for the classification of the face image gender. The support vector machine classifier is used for the gender classification.

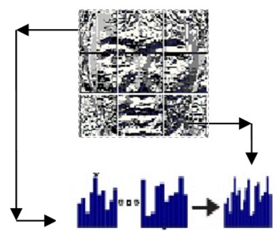

Figure 7 Local Binary Pattern image histogram

2.3.3 Principal Component Analysis (PCA)

In the paper, the gender classification performed using support vector machine. The gender classification is carried out using features based local binary pattern and local direction pattern. The local directional pattern represents image features more accurately as compared to the local binary pattern. The data dimension reduction is done by using principal components analysis. It reduces the size of high dimension data by removing the unimportant part of the data[20]. The gender classification is performed by combing the principal component analysis and local direction pattern. The principal component analysis transforms the image data into the feature space and represented by the orthogonal axis vectors these are called as principal components of the image data. The feature vector is arranged in the direction of the maximum variance. Thus, the principal components of the image data are arranged in the decreasing order of the variance i.e. The first principal component represents the maximum variance in the data set than the second component etc. The principal components are calculated with the eigenvector and eigenvalues[13]. The eigenvector of the principal components is arranged in the decreasing order of the eigenvalues the eigenvector with small eigenvalues can ignored thus, principal component analysis used for representing in reduced size by eliminating the redundant data. In this study of the gender classification, the face image features are calculated using the local directional pattern and further the dimensions of these feature vectors are reduced by applying the principal component analysis. The result shows that the local directional pattern(LDP) and principal component analysis(PCA) is improved as comparing to the only LDP and LBP as shown in figure 13

2.4 Support Vector Machine

Support vector machines are based on the supervised machine learning technique for the classification. The support vector machine classification technique is represented as linear or nonlinear classifier machines. The support vector machine is used for many applications in the areas of machine learning. The support vector machines have better ability for generalization of which is the main objective of the support vector machine. The support vector machines basically designed for classification and can also be used for the regression problems.

2.4.1 Statistical Learning Theory

The statistical learning is a framework for the solving the problem of the predictions, decision making for the data set. The statistical classification problem is the solution of the problem given in terms of the hyper plane separating the classes of the different categories. The hyper planes are selected such that it separates classes of the different sets into the different classes. The classification problem is given as a training data set $(x_1,y_1),(x_2,y_2)$ ……….$(x_n, y_n))$ and the class label's are y=(+1,-1). The support vector machine classifier is trained for the known classes so is called as supervised machine learning. When unknown data is given, the support vector machine predicts the class of the test data according to the training of the dataset.

The support vector machine classifier is a class of supervised machine learning algorithm that learns by examples and classifies the object into one of the class of the object. The support vector machine has been applied to diverse problems, including pattern recognition, regression and object classifications. The support vector machine model represents examples as a point in the space. The support vector machine model divided examples into different categories of the classes by the clear gap between each class. The generalized problem of object classification is to assign particular object class category for an unknown object. The objects of the two different categories are separated by the hyper plane as shown in figure 8. The hyper plane separated the two data classes. The green color circle represents data class 1 and white color circles represents the data class2 . The data which is near to the hyper plane are called as support vectors .

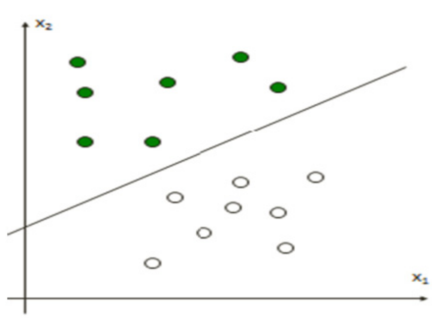

Figure 8 Support Vector Machine

Mathematically, this hyper plane is represented by the discriminating function or the decision boundary function. The figure 8 shows graphical representation for the support vector machine. The theoretical background of support vector machine is described in the following paragraphs.

A support vector machine is basically used for two class problem. However, it could be used for multiclass problem by treating each single class problem as a classification problem separately. The support vector machine works on the support from the data points in the space.

Consider the problem of classification of the training vectors into two classes. The training data set is represented as

$$\left(x^i, y^i\right), x^i \in R^i, y^i \in (+1,-1), i = 1,2,..,N \tag{3}$$

$(x^{(i)},y^{(I)})$ is set of N training simples, $x^{(i)} \epsilon R^n$ and $y^{(i)}$ are the class labels {+1,-1}. The hyperplan is a décision boundary which separates the two classes. The équation of the hyperplane function written as

$$f(x) = w^T x + b \tag{4}$$

Where w is a weight vector and b is a bias which represents the distance of the plane from the origin. When the bias b is replaced with w_0 then the equation (4) becomes

$$f(x) = w^T x + w0 \tag{5}$$

The linear support vector machine is a binary classifier problem which classifies objects as member of the class or absent from the class as shown in the following equation.

$$f(x) \geq 1 \; for all \; y^{(i)} = +1 \tag{6}$$

$$f(x) \leq -1 \; for all \; y^{(i)} = -1 \tag{7}$$

If the training data is linearly separable, we can select a two hyper plane, which separated data in two different planes and there are no points between them. In practice, nonlinear data may be used, to process nonlinear data support vector machine with kernel functions are used. The nonlinear classification is performed in the two steps. In the first step, training data are transformed into higher dimension using nonlinear mapping function, it is called as kernel function. The kernel function k(x, x') given as k(x, x')=Φ(x^T).Φ(x'). The online mapping function is Φ and represented as.

$$f(x) = w^T \Phi(x) + b \tag{8}$$

The two class support vector machine can be extended to the multiclass classification problem.

The multiclass support vector machine two types of approaches are used one versus one and one versus all. The one versus one transforms the multi classification problem into a series of binary classifiers that can be trained by the several support vector machines. The each classifier give vote to winning class and final class is identified with the maximum votes. In case of one versus all each class is trained one at a time and class which gives largest values chosen as the class of the object. In this paper, the linear support vector machine is used for the two class problem which decides the size as a class of the face.

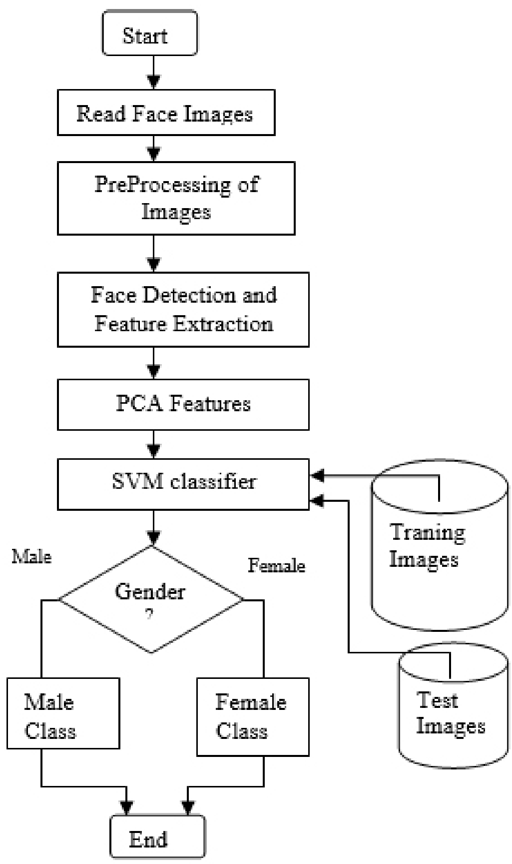

Figure 9: Flow Chart for Gender Classification

2.5. Result Analysis & Discussions

The gender classification is performed using the local directional pattern. The local directional pattern is applied on the image with the 3x3 matrix. The spatial information is encoded in the local directional pattern. The local directional pattern gives better edge information compared to the local binary pattern. The local directional pattern(LDP) for the face is calculated using krisch edge mask. This krisch mask forms the feature vector of the image. The principal component analysis(PCA) technique is used to reduce the size of the feature vector. The results show that, gender recognition accuracy is improved using the local directional pattern and principal components analysis. The feature vector using local binary pattern(LBP) also calculated for comparison of the gender classification. The four face image data sets are used for the gender classification. The dataset includes Caltech, Lfw, Yale and Orl[22-25]. The result of the gender classification is shown in figure 13 and the ROC curve analysis are shown in the figure 10. The ROC curve analysis is performed for the face image dataset as shown in the table 1 for the gender classification. The more accuracy is achieved with the Caltech face dataset as compared to the lower with the Yale face data set. The result of the facial gender recognition with the facial expression is shown in figure 12. The face images of the lfw data set are shown in figure 11. The accuracy of the gender classification is reduced in case of the facial expression.

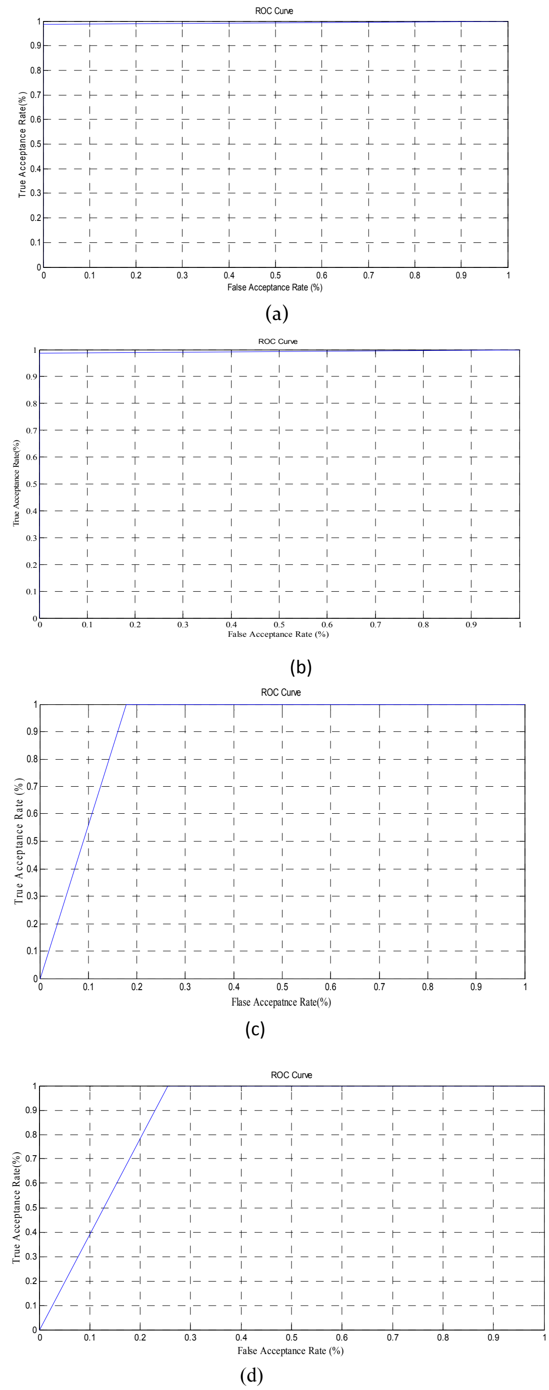

Figure 10 : Roc Curve for Gender Classification
a) Caltech b) Orl c) Lfw d) Yale

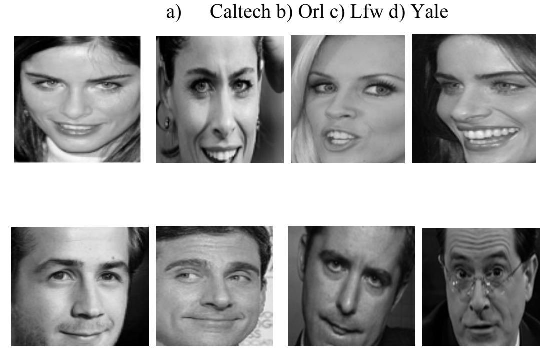

Figure 11. Face expression Images [25]

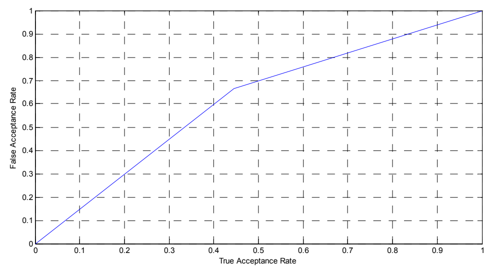

Figure 12. Roc curve for face(expression) gender classification

Table 1: Gender Classification

Sr no	Face Dataset	Male	Female	LDP+ PCA	LDP	LBP
1	Caltech	200	100	98	96	94
2	ORL	200	150	97.3	95.5	95
3	Lfw	200	150	96	93	90
4	Yale	200	100	94	90	91

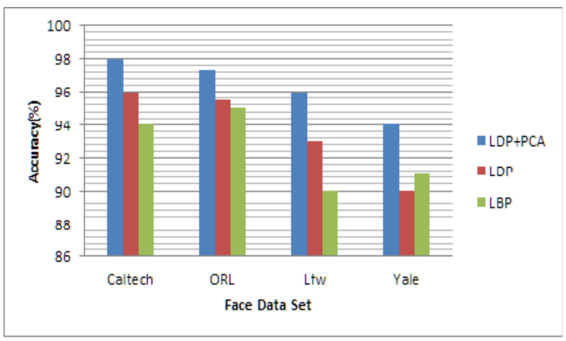

Figure 13 Gender Classification Result

3. Conclusion

In this paper, the gender classification method based on the local directional pattern is proposed. The gender classification has many applications like human computer interface and other industrial applications. The experiment is performed on the four different face dataset i.e. Caltech, Lfw, Yale and Orl. The average gender classification accuracy is 96 %. The three different methods are used to perform the gender classification using local binary pattern(LBP), Local Directional Pattern (LDP) and the use of the principal component analysis (PCA) for the feature vector data reduction. The graph of the result is shown in figure 13. The result shows that, the face gender classification is improved using the LDP features and PCA.

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[25] http://vis-www.cs.umass.edu/lfw

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